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Detecting Suicide Risk From Wristworn Activity Tracker Data Using Machine Learning Approaches

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DETECTING SUICIDE RISK FROM WRISTWORN ACTIVITY TRACKER DATA USING MACHINE LEARNING APPROACHES

by

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Dedication

This thesis work is dedicated to my late loving grandfather

Sunkara Siva Rama Krishnaiah garu and Dr.A.P.J Abdul Kalam garu

Who inspired me to do research.

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List of Abbreviations

AUC	Area Under the Curve
FN	False Negatives
FP	False Positives
FPR	False Positive Rate
ROC	Receiver Operating Characteristics curve
SVM	Support Vector Machine
TN	True Negatives
TP	True Positives
TPR	True Positive Rate

ABSTRACT

DETECTING SUICIDE RISK FROM WRISTWORN ACTIVITY TRACKER DATA USING MACHINE LEARNING APPROACHES

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Suicide is a prevalent cause of death worldwide and depression is a primary concern of many suicidal acts. It is possible that an individual during depression never has any suicidal thoughts at all. On the other hand, some individuals in stable condition with no apparent symptoms of depression feel urges to commit suicide (suicidal ideation). Many such individuals never let anyone know what they are feeling or planning. Suicidal ideation considered an important precursor to suicidal acts.

Detecting the suicide risk in individuals with mood disorders is a major challenge. The current clinical practice to assess suicide risk in these vulnerable individuals based on structured or semi-structured psychiatric interviews is inadequate as many of the suicidal behaviors often occur unpredictably especially during apparent clinical remission. Furthermore, some of these individuals are unable or unwilling to share their experiences with clinicians. An objective

feature that can continuously monitor risk of suicidal thoughts would be advantageous in such situations.

Our research focused on finding objective features in activity data for detecting suicidal ideation in a sample of individuals diagnosed with Bipolar I, Bipolar II, or Unipolar who were currently in a euthymic state. Euthymic state is considered a non-depressed and reasonably positive mood state, but individuals in this state may still have suicidal ideation. Hence, our work explores detecting risk of suicidal thoughts in euthymic individuals in a group of mood disorder subjects using machine-learning approaches.

Statistically significant differences were observed between activity features of euthymic and depressed individuals. A strong negative correlation was observed between activity feature vulnerability index with self-rated suicidal ideation. This study demonstrates that we can use machine learning techniques to detect risk of suicide in euthymic individuals from activity data. The main advantage of using activity data is that it would be cost effective, since many people commonly use activity trackers.

CHAPTER ONE

INTRODUCTION

Suicide is one of the major public health concerns in the United States and around the world. According to the World Health Organization, over 800,000 people die every year by suicide [1]. The major problem in preventing suicide is that some people having suicidal tendencies do not seek help and unwilling to share their feelings or pain even with their family or friends. Current clinical practices to detect suicide risk are often subjective in nature, leading to different opinions based on individual clinicians. Furthermore, suicidal behaviors can appear suddenly when individuals are considered apparently in stable conditions [2]. Hence there is a need for tracking suicidal ideation continuously in real time to detect daily or even hourly variation of suicidal ideation. With the recent advancements in psychology, medicine and engineering; attempts were made to detect suicide risk objectively. However, many of such approaches are not feasible for real time detection and tracking of suicidal ideation. In this work, we propose a method based on advanced signal processing and machine learning approaches to detect risk of suicidal thoughts in real time using wrist worn activity tracker devices. Our approach might help clinicians to detect suicide risk thus reducing the risk of subjective biases that might help clinicians for the effective management and treatment of individuals with suicidal ideation.

Therefore, our objective and framework include:

(1) To study whether linear and nonlinear features of activity data are significantly different in euthymic individuals who are not suffering from symptoms of depression compared to individuals that are in major depression. When individuals meet criteria

for major depressive disorder, Bipolar I, Bipolar II or Unipolar care is given to these individuals to assess the underlying mental health conditions as well as their suicidal ideation. However, when a previously depressed individual is in a stable condition, generally they are considered equivalent as normal state. However, if such individuals have high level of suicidal ideation, they are likely to attempt suicide. Hence, it is important to detect the level of suicidal ideation in such individuals.

(2) To study whether features derived from activity data be employed in machine learning methods to classify euthymic individuals and depressed individuals.

(3) Finally, to study whether machine learning approaches with features derived from activity data can be employed to detect high suicide risk individuals in real time.

AMI-128K Mini-Motion logger (Ambulatory Monitoring, Inc. [AMI], Ardsley, NY, USA) has been used in this work to track daily activity. Feature extraction and machine learning algorithms were developed using MATLAB (The Math Works, Natick MA).

1.1 Wearable activity trackers

Number of wearable devices like Fitbit, the Garmin watch, and the Apple watch are presently being used as fitness trackers. These devices use embedded sensors to continuously monitor physiological signals such as gross body movement (activity), heart rate and skin temperature. These signals are then used to provide information regarding sleep-wake cycle, step count and other health statistics which might help to monitor the wearer's health. One such signal that we employed in our work was activity data (actigraphy).

Actigraphy is the measurement of motion tracked using miniature accelerometers to monitor daily activity and sleep patterns. It mainly measures our motor activity i.e. muscles which causes motion in our body. These motion patterns are displayed as actograms. These data were used to extract information about 24hr circadian rhythms as well as sleep and wake patterns. Actigraphy has been used in many studies on various disease states such as sleep disorders, mood disorders and depression [3].

1.2 Signal processing methods

The Fourier transform is a traditional and powerful technique that has been extensively used in signal processing. The Fourier transform maps a signal in the time domain to its equivalent frequency-domain representation. However, it has only frequency resolution and lacks time resolution; means even though we detect all the frequencies in the signal we don't know when they are present. The Fourier transform is very useful if the signal is stationary and from a linear system, but most physiological systems are nonlinear and corresponding signals are non-stationary in nature. In addition, we do not know *a priori* what important information that signal has and at which scale. Hence, we cannot use traditional Fourier transform techniques to process physiological or biomedical signals. We employed wavelet transform in which we use wavelets that are well localized in both time and frequency domain [4]. Its variable-size windowing technique and vast variety of wavelet functions makes it suitable to apply for non-stationary signals. We employed this transform to extract amplitude at multiple time scales to understand the activity data and its relation to suicidal ideation.

1.3 Machine learning approaches

Machine learning techniques have been employed widely in various fields because of their ability to learn and make decisions from data. And we do not need to explicitly program again, once our training process completes [5]. Four types of learning processes have been primarily used in machine learning: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning.

1.3.1 Supervised learning

Supervised learning uses labelled data to predict its output. Generally, input data are termed predictor variables or features, and output data are termed as target variables. In supervised learning the classifier learns about target variables directly from features [6]. Suppose we want to distinguish between lemons and grapes. If size is small and color is either green or black, we can classify the unknown objects as grapes; if size is medium and color is yellow, we can classify them as lemons. In this scheme, the target variable is mapped as a function of size and color (features). If the target variable consists of categories like above example, such type of learning is called classification. If the target variable is continuous, such as predicted stock prices, the process is called regression type learning. Random forest, support vector machine (SVM), liner regression and logistic regression are some of the examples of supervised learning models.[7]

1.3.2 Unsupervised learning

Unsupervised learning does not use any labeled data. In this, classifier tries to find the similarities between the features and then group them into clusters [8]. Grouping people based on their ethnicity, age, or height are examples of classification using unsupervised learning. K means, hierarchical clustering and self-organizing map are some of the examples of unsupervised learning.

1.3.3 Semi-supervised learning

Semi-supervised learning uses a mixture of supervised and unsupervised learning techniques, employing both labeled and unlabeled data. Text classification [9] and lane finding from GPS data are examples of semi-supervised learning.

1.3.4 Reinforcement learning

In reinforcement learning, software agents learn to react and interact with their environment. Reinforcement learning agents will automatically determine how to optimize their behavior. There will be rewards or punishments depending upon how successfully the task was accomplished. Chess-playing programs and driverless cars are examples of reinforcement learning [10].

1.4 Organization of Thesis

This thesis is divided into five chapters. Chapter 2 gives a brief overview of previous works which relate to the current study. Chapter 3 provides information about methods employed in this work-implementation of wavelet methods, decision trees and support vector machines. Chapter 4 provides details of our algorithm implementation and results of classifications obtained in this work. Chapter 5 presents conclusions and suggestions for future study.

The intellectual merit of this interdisciplinary work is the application of engineering principles, in particular advanced signal processing and machine-learning approaches, to address a major problem in psychology. The significance of this work includes integration of approaches from two fields of study that are diverse and often considered as distinct to solve a major public health problem. The broader impact of this work is that systems and methods developed in this wok may be useful for solving not only suicidal ideation related to mood disorders but also for understanding broader psychopathologies related to postpartum depression, addiction, post-traumatic stress disorder and other mental health conditions.

CHAPTER TWO

BACKGROUND

We briefly describe past attempts to identify suicidal behavior using machine learning approaches. One of the major challenges we faced for research in this area has been collecting real-time data in a timely manner to prevent future attempts. In recent years, social networking sites like Facebook and Twitter have been used by many people, and large amounts of data related to any specific topic of interest likely to be available. Many research studies have been conducted to identify suicidal content in these online platforms using machine learning techniques and natural language processing. Jashinsky et al. proposed a method to detect suicide risk factors with twitter data [11]. This paper discusses identification of keywords and phrases in tweets which may indicate suicide risk content. Using the Twitter streaming application programmer interface, they analyzed geographically-based tweets and compared them with suicide rate statistics in the United States. The results obtained showed kappa $\kappa = 0.48$, which is of reasonable accuracy. This is a classification metric which compares observed accuracy with an expected accuracy. Classifier performance with $\kappa \geq 0.75$ indicates very good accuracy; $0.40 \leq \kappa < 0.75$ indicates good accuracy; $\kappa < 0.40$ indicates poor performance. In another study Burnap et al. used a rotation forest machine learning algorithm to distinguish between worrisome language (possibly containing suicidal content) and normal language in Twitter; they report an accuracy of 0.69 [12]. Braithwaite et al. used decision tress to find people who appear to be at high risk of suicide based on their Twitter feeds; they showed an accuracy of 0.75 [13]. Thompson et al. used veteran medical records and postings in Facebook of respective patients to identify suicide risk content [14] . The results showed an accuracy of 0.69 to identify text-based signals using supervised machine learning.

Li et al. obtained information from Chinese web forums and other social networking sites and using machine learning proposed a framework to automatically detect suicide risk content [15]. Pestian et al. studied suicidal thought markers using verbal and non-verbal features [16]. They recorded audio signals from patients during the interviews and along with medical transcriptions extracted single word and pair words related to suicide risk. These words were used to form a dictionary. Fundamental frequency, square of the amplitude, difference between the first and second harmonics has been obtained from their audio recordings. Using both word dictionary and audio signals as features, they were able to classify suicidal subjects and control subjects using support vector machine with an accuracy of 0.83.

Laksana et al. studied suicidal thought markers using nonverbal feature by extracting facial behavior during interviews [17]. All the subjects were asked pre-determined questioner related to their emotional state and smiling, frowning, head motion behavior and eyebrow raising were extracted from their facial expressions. Duchenne Smile Percentage, slope of smile onset/offset, frowning behavior were taken as features and using support vector machine approach suicidal subjects were identified with an accuracy of 0.42.

All the above approaches look promising however some individuals with high level of suicidal ideation are unwilling or unable to communicate their suicidal thoughts to a clinician or a caregiver, which makes it difficult to identify suicidal risk in such individuals. Hence there is a need of detecting suicide risk noninvasively and continuously, which can help even if the individuals are non-communicative. Some of the recent studies recently focused on noninvasive methods to detect suicide behavior.

Just et al. studied alterations in functional magnetic imaging of neural signatures to assess the suicide risk [18]. Voxels (pixel in the display of MR image) in clusters that are common between suicidal and non-suicidal groups and voxels from unshared clusters were taken as features, using gaussian naive base classifier classification of suicidal attempters were identified with an accuracy of 0.91. However, this approach is difficult to implement in real time for tracking suicidal ideation. It would be helpful if we can track suicidal ideation continuously and noninvasively.

Indic et al. studied objective markers in major depression subjects which can identify suicidal risk [19]. Bipolar and unipolar subjects were distinguished using nonlinear feature vulnerability index with a sensitivity of 91.7%. However, this nonlinear feature or any other features not been employed to develop methods for accurately detecting risk of suicide in real time. In this work, we propose to use such nonlinear as well as linear features of activity data in the machine learning approaches to detect suicide risk in real time.

CHAPTER THREE

METHODOLOGY

This chapter deals with methods used for preprocessing of data to extract features that will be used in machine learning. It also discusses about machine learning techniques used in this work which include decision tress and support vector machines.

3.1 Preprocessing of data

Preprocessing of data is very important because in general collected data can contain noise and data gathering methods are loosely controlled which results in out of range values, missing values or impossible combinations. We took activity data continuously and noninvasively using a wrist worn wearable device for 3 days from 58 patient-subjects diagnosed with mood disorders within the Bipolar-illness spectrum based on diagnostic and statistical manual of mental disorders(DSM-5)[20].Bipolar disorder type 1(BD-I) of N=30 subjects, bipolar disorder type 2 (BD-II) of N=23 subjects, and unipolar disorder (UPD) with stable hyperthymic/cyclothymic temperaments of N=5 subjects were present in the data. Patients were recruited as inpatients at the Section of Psychiatry of the University of Parma, Italy, and semi-structured interviews were taken by psychiatrist and euthymic and depressed subjects were identified.

Activity data collected for 72 hours from 58 subjects N=33 are in euthymic and N=25 are in depression. The technical limitation of the device prevented us getting data for more than 72 hours due to insufficient memory. Traditionally, we assume signals of infinite duration and apply the Fourier transform to obtain amplitude vs frequency information. However, in real time, signals have finite duration. Most physiological signals are nonstationary in nature with amplitude and frequency varying with respect to time. Wavelets are a powerful tool for such applications. We derived features from activity data by the application of the continuous wavelet transform. A wavelet is a localized waveform (known as a mother wavelet) which lasts only for a while. Information in the data are captured using a scaled as well as a translated version of the mother wavelet. Using the wavelet transform, we convert a signal into another form in which its features may be studied in a clearer manner. Wavelets are also very good at both time and frequency localization[21] [22]. In this work, in particular we have to capture level of amplitude fluctuation in activity data at multiple time scale that occurs in entire 72 hrs. of data. By the application of continuous wavelet transform to a discrete set of data using Morlet wavelet function as a mother wavelet we determined the amplitude fluctuations at multiple time scales to accurately derive the features[23]. The Morlet wavelet function is appropriate for capturing signals with periodic oscillations (for example ~24 hr. circadian rhythms).

3.2 Decision tree

The decision tree is a widely-used classifier. The first use of a tree-based decision system was used in artificial intelligence in the 1960s [24] [25] . The decision tree analyzes and extracts valuable rules as well as relationships from data sources. Since the decisions are made at multiple levels, these supervised classifiers are more efficient than single stage classifiers. It uses tree structure to make decisions. Tree structure consists of root node, child nodes and leaf nodes; each node makes decision based on its attribute value of data.

One of the most commonly used decision tree is binary tree, which uses tree growing approach for classification. In binary trees, a case traversing to the left child is true while a case traversing to the right is false. Nodes in non-binary trees have one child for each possible attribute value. A case traverses down the tree based upon its data until reaching a leaf node at which point the tree can return a final decision or classification for that case. For example, if a decision tree is to classify flowers, each node make decision based on attributes of flower such as petal length and petal width.

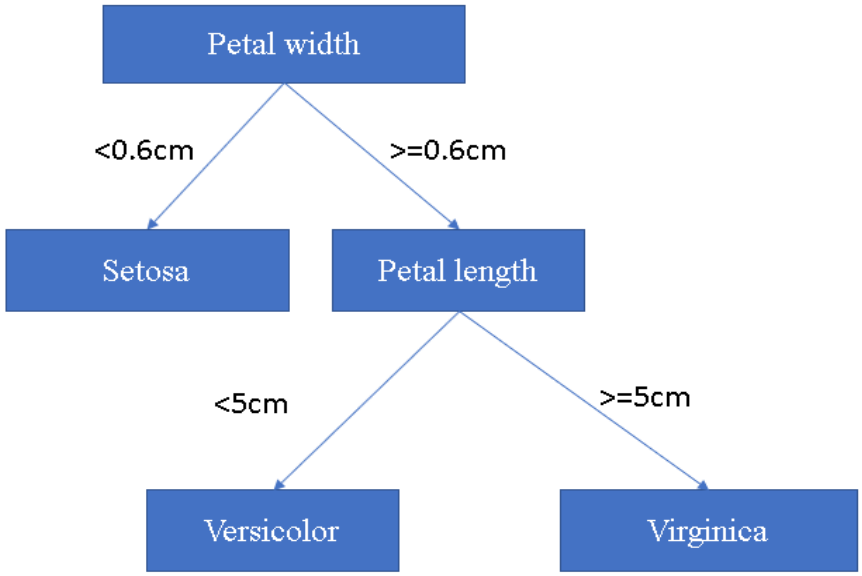

Figure 1: Example of decision tree

Figure 1 shows a basic decision tree for classifying flowers setosa, versicolor, and virginica. Here, the root node is petal width. If petal width is less than 0.6cm, the root node will make decision and the flower is classified as setosa. On the other hand, if petal width is greater than or equal to 0.6cm, both versicolor and virginica are possibilities. The second decision node then discriminates between the two based petal length; if the petal length is less than 5cm, the classification is versicolor; otherwise, the classification is virginica. For such a small data set, the tree might seem obvious. When more features are introduced, the problem of classification becomes much more complex. The difficulty in utilizing decision trees lies in their construction.

3.3 Support Vector Machine

Support Vector Machine (SVM) is a supervised learning method which is widely used for classification and regression analysis [26] [27]. Basically, SVM is a linearly-separable two class problem which works on the principle of finding an optimal plane to separate two classes.

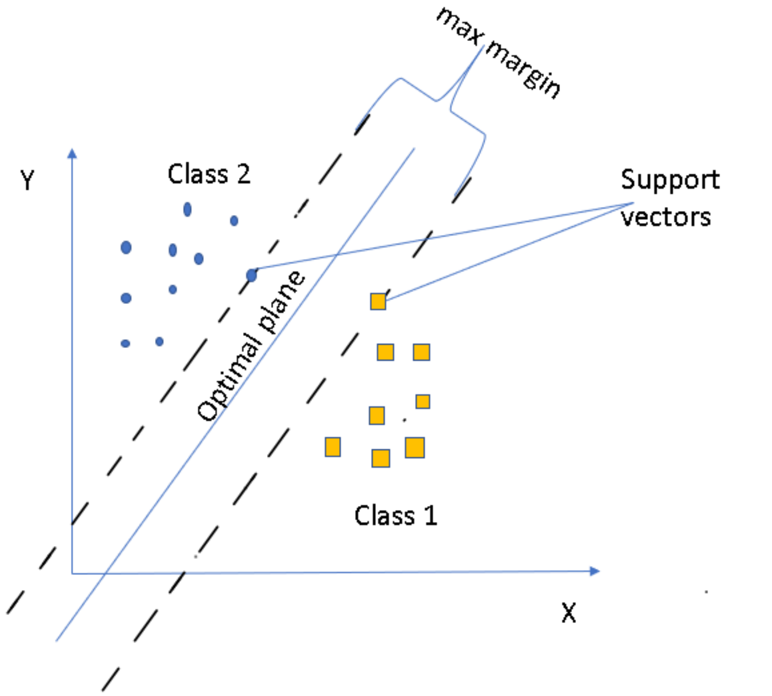

Figure 2: Illustration of linear SVM

In the case of linear SVM, if more than one plane is available to separate the data, then the plane which has the maximum margin between two classes of data will be selected as shown in Figure. 2. This is known as the optimal plane. Boundary points which separate two classes are called support vectors.

Suppose the given data are no longer linearly separable. Then SVM finds multiple planes that accurately separate the data. This becomes much more complex and challenging as the data become less separable, thus requiring more planes for accurate separation. Consider the example shown in Fig. 2 in which the given data points are not linearly separable. SVM methods solve this obstacle by increasing the dimensionality of the training data so that a single hyperplane can accurately separate the data [28].

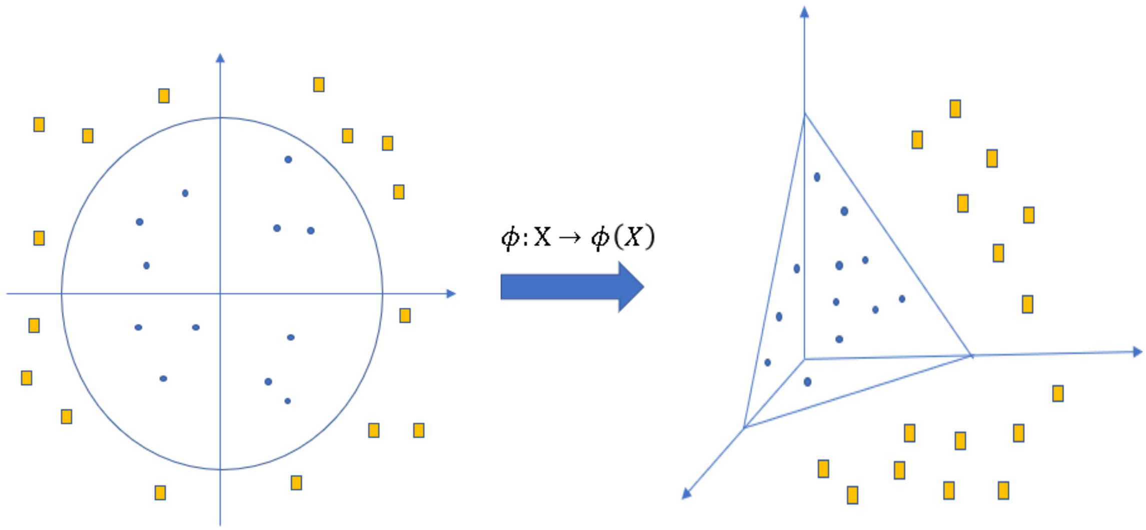

Figure 3: Illustration of nonlinear SVM

Here ϕ(X) is called feature space representation. In above case, this optimal plane is projected to higher three-dimension (3D) space. This technique is commonly known as kernel trick [29]. The Gaussian radial basis kernel is a commonly-used kernel. The kernel basis function of Gaussian SVM is given by $k(x,y) = exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right)$; here x and y are the feature vectors, and σ is a free parameter[30] [31].

The nature and size of the data will determine whether to use linear SVM or nonlinear SVM. In general, linear SVM is used if the number of features is large when compared to number of training samples; nonlinear SVM is employed if both the number of features and number of training samples are fewer and when given data is not linearly separable.

3.4. Performance metrics for classifiers

After feature extraction, selection and implementation of a model, and obtaining an output in the form of a probability or a class, the next step is to determine the model effectiveness based on metrics using test datasets. For classification problems, the confusion matrix, accuracy, area under the curve (AUC) of receiver operating characteristics curve (ROC) obtained using sensitivity and specificity are generally used metrics.

3.4.1 Confusion matrix

The confusion matrix is one of the most intuitive metrics used for finding the correctness and accuracy of the model. It is used for classification problem where the output can be of two or more types of classes. For example, we are solving a classification problem where we are predicting whether a person is having suicidal ideation or not. Our target variable is indicated by 1 in case if person is having suicidal ideation, 0 if person is not having suicidal ideation. The confusion matrix gives a table with two dimensions actual and predicted and sets of classes in both dimensions. Our actual classifications are rows and predicted ones are columns.

Table 1: Confusion Matrix

	Predicted	
Actual	Positive (1)	Negative (0)
Positive (1)	TP	FN
Negative (0)	FP	TN

Terms associated with Confusion matrix:

1.True Positives (TP): True positives are the cases when the actual class of the data point was 1 (True) and the predicted is also 1 (True). In our example, the case where a person is actually having suicidal ideation (1) and the model classifying his case as suicidal ideation (1) comes under TP.

2. True Negatives (TN): True negatives are the cases when the actual class of the data point was 0 (False) and the predicted is also 0 (False). In our example, the case where a person NOT having suicidal ideation and the model classifying his case as no suicidal ideation comes under TN.

3. False Positives (FP): False positives are the cases when the actual class of the data point was 0 (False) and the predicted is 1 (True). False is because the model has predicted incorrectly and positive because the class predicted was a positive one (1). In our example, FP occurs when a person is NOT having suicidal ideation, but the model misclassifies the individual.

4. False Negatives (FN): False negatives are the cases when the actual class of the data point was 1 (True) and the predicted is 0 (False). False is because the model has predicted incorrectly and negative because the class predicted was a negative one (0). In our example, a person having suicidal ideation but who is misclassified as not experiencing suicidal ideation comes under FN.

The ideal scenario would be that the model should give no False Positives and no False Negatives. But no model will be 100% accurate. We know that there will be some error associated with every model that we use for predicting the true class of the target variable. This will result in False Positives and False Negatives. There is no hard rule that says what should be minimized in all the situations. It depends on the requirements and the context of the problem we are trying to solve. Depending upon the nature of the problem, we may wish to minimize either False Positives or False Negatives.

3.4.2. Accuracy

Accuracy in classification problems is the number of correct predictions made by the model over all kinds predictions made.

Table 2: Accuracy

Actual	Predicted	
	Positive (1)	Negative (0)
Positive (1)	TP	FN
Negative (0)	FP	TN

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}$$

In the numerator, are our correct predictions (True Positives and True Negatives) (marked as green in the table above) and in the denominator, are the kind of all predictions made by the algorithm (right as well as wrong ones). Accuracy is a good measure when the target variable classes in the data are nearly balanced.

3.4.3 Receiver Operating Characteristics (ROC)

Receiver Operating Characteristic (ROC) curve is commonly used way to visualize the performance of a binary classifier. By varying different thresholds, we determine the True Positive Rate (TPR) as the ratio of true Positive to total Positive (also known as sensitivity) and the False Positive Rate (FPR) as the

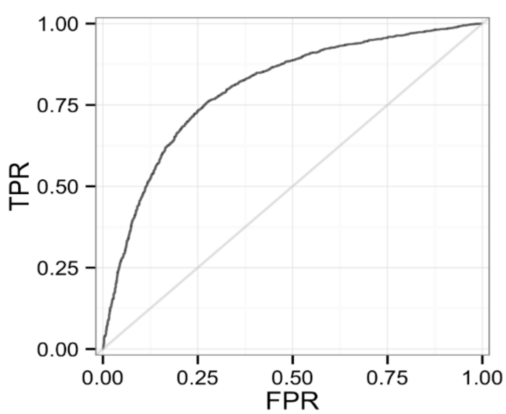

Figure 4: A sample ROC curve

ratio of False Positives to total Negatives also known as 1- Specificity. Specificity is ration of true Negative to total negative. ROC curve is a plot between TPR and FPR. A perfect classifier will have an AUC as 1. If our classifier gets AUC as 0.5, then that model can only predict correctly half of the given data set. Any AUC value less than 0.5 indicates a poor predictive model. A representative ROC curve is given below in figure 4 which has an AUC of 0.75.

CHAPTER FOUR

IMPLEMENTATION AND RESULTS

In this work, we studied

(i) Whether linear and nonlinear features of activity data are significantly different in euthymic individuals compared to individuals during depression.

(ii) Whether activity features can be employed in machine learning methods to classify euthymic and depressed individuals.

(iii) Whether activity features can be incorporated in a machine learning framework to detect high suicide risk individuals in real time irrespective of their conditions (euthymic or depression)

The linear features include mean as well as variance of activity data, and wavelet derived maximum power. The nonlinear feature includes the scaling behavior estimated at multiple time scales using the same wavelet transform and represented in a comprehensive form using an index called vulnerability index (VI). Thus, we are using four features such as (i) mean, (ii) variance, (iii) Power and (iv) VI to build the machine learning algorithm.

Prior to building the machine learning algorithm, we did a bivariate analysis to understand whether these features are significantly different between euthymic and depression. Then we developed three machine learning models to differentiate between euthymic and depressed subjects: decision tree, linear support vector machine, and non-liner support vector machine with Gaussian kernel algorithms. We then applied the same framework with the same features to detect high suicide risk subjects in euthymic condition and subsequently we applied the same classifier to study the accuracy of detection of high suicide risk subjects during depression. The machine learning algorithms are developed using MATLAB 2015 with 5-fold cross validation for testing.

4.1 Feature extraction

Activity data collected for 72 hours from 58 subjects out of which 33 are euthymic and 25 are in depression. We did not use data from any healthy individuals as such comparisons have been made before [32]. However, to get an idea of activity profiles, we are presenting in Figure 5 the activity data collected from three individuals, one is a normal healthy individual, other one is in euthymic condition and third one is in depression.

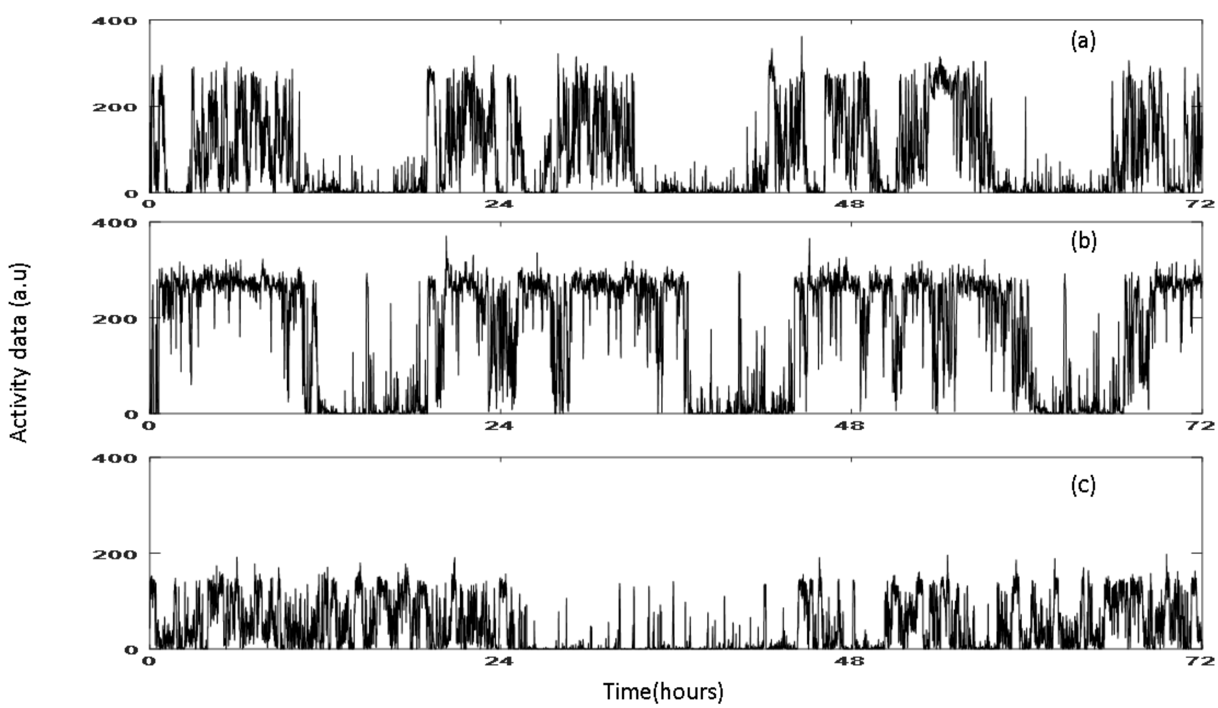

Figure (5): Activity data of (a) healthy, (b) euthymic and (c) depressed individuals

Activity data represented in auxiliary units

Activity data in the healthy subject follows the circadian rhythm (24-hour pattern) and includes strong motor amplitudes. In this example, the euthymic subject also has a strong circadian rhythm however this is not the case always in these subjects. Depending upon their underlying mental health conditions, these subjects may or may not show a robust circadian rhythm. Application of the wavelet transform will enable us to capture all the fluctuations happening in these subjects at multiple time scales. In the depressed subject, as shown in Figure 5, there is no robust circadian rhythm and motor amplitude is significantly reduced when compared to the healthy subject.

To obtain predominant power from the global wavelet spectrum (GWS) and VI from amplitudes at multiple time scales, we applied continuous wavelet transform with Morlet function as a mother wavelet [33]. We calculated GWS and amplitude at multiple time scales. These amplitudes followed a long tail distribution and the shape of the distribution was obtained using a gamma function fit. We calculated VI [19] by integrating the shape parameter from 0.2hr to 1.5 hr. from all the subjects. From the GWS, we detected the peak value as the predominant power. The mean and variance were calculated using the standard approach. Thus, we obtained four features for all the subjects using 72-hour data. Detailed information about wavelet analysis can be found in appendix A.

4.2 Comparison of activity features between euthymic and depression: A bivariate analysis

The 58 patient-subjects included 42 women (72.4%) and 16 men (27.6%), of average age 47.9±13.3 years at intake (median=45.5; inter-quartile range [IQR], 38-60 years; range, 22-73 years). Patient-subjects in euthymia vs. clinical depression did not differ as to gender distribution and age at intake. With regard to clinician-administered rating scales, as expected from inclusion diagnostic criteria, *Hamilton Depression* scores [34] were significantly higher in clinical depression than during euthymic intervals, whereas Koukopoulos scale [35] for depressive mixed states were comparable in the two groups. The latter findings might indicate that both moodpsychomotor lability/instability and dysphoric emotional reactivity/resonance could be core disturbances in bipolar spectrum disorders, constantly underlying psychopathological phenomenology, and never receding into the background even in euthymic phases. All the subjects reported suicidal ideation. All the features derived from activity data except mean showed statistically significant differences between the two groups including significantly lower VI (***p***=0.002) and higher variance (***p***=0.004) as well as higher GWS (***p***=0.03) values in clinical depression than euthymia.

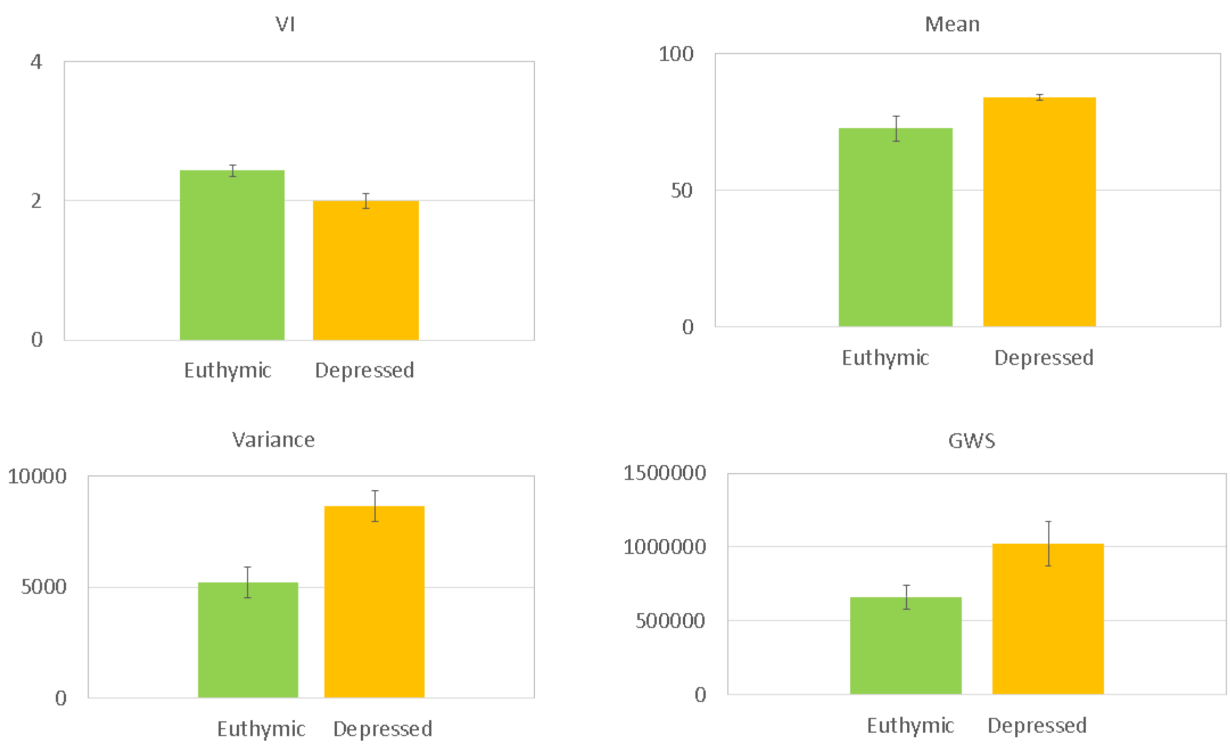

Figure (6): Statistical differences of features between euthymic and depressed subjects

We examined the Pearson correlation of features with self-rated suicidal ideation, which was obtained from clinical assessments. We found a strong association between VI and the self-rated suicidal ideation with a correlation of (**r** = -0.73, **p** <0.0001). We found that VI is negatively correlated with self-rated suicidal ideation means a low VI value indicated high risk of suicidal thoughts.

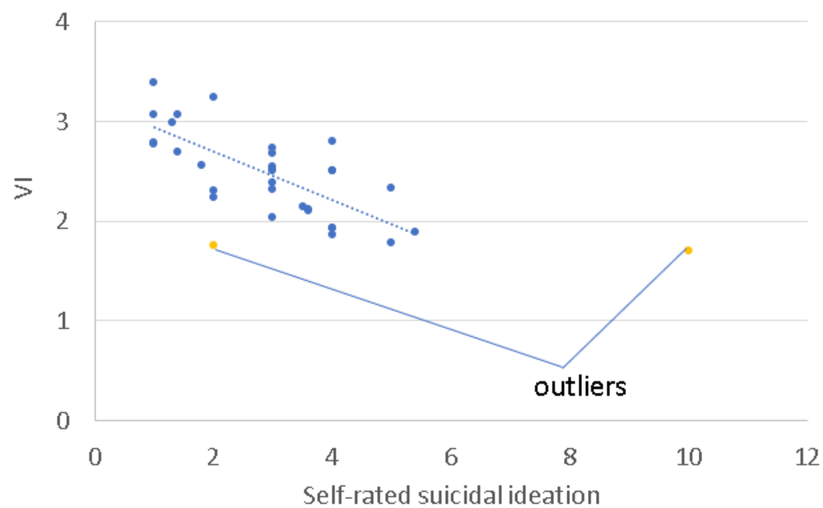

Figure 7: Plot of VI and self rated suicidal ideation in euthymic subjects. after removing two outliers with Cooks'd [36] the correlation obtained as ***r*** = -0.73, ***p***<0.0001

4.3 Classification of euthymic vs depressed: A machine learning approach

As mentioned before, we employed decision tree, linear SVM, and nonlinear SVM to classify euthymic and depressed subjects. Using a decision tree classifier as shown in the confusion matrix given in Table 3, we were able to detect 27 euthymic subjects out of 33 whereas we could detect 16 depressed subjects out of 25. The TPR was 0.81 and FPR was 0.36. We obtained an accuracy of 74.1% and AUC of 0.76 by using this classifier.

Table 3: Confusion matrix of euthymic vs depressed using decision tree

Actual	Predicted	
	Euthymic	Depressed
Euthymic	27	6
Depressed	9	16

Using linear SVM as shown in Table 4, we were able to detect 27 euthymic subjects out of 33 while we detected 13 depressed subjects out of 25. The TPR is obtained as 0.81 and FPR is obtained as 0.48. We obtained an accuracy of 69% and AUC of 0.75 by using this classifier.

Table 4: Confusion matrix of euthymic vs depressed using linear SVM

Actual	Predicted	
	Euthymic	Depressed
Euthymic	27	6
Depressed	12	13

Using nonlinear SVM with Gaussian kernel as shown in Table 5, we were able to detect 27 euthymic subjects out of 33 whereas we could detect 18 depressed subjects out of 25. The TPR is obtained as 0.81 and FPR is obtained as 0.28. We obtained an accuracy of 77.6% and AUC of 0.77 by using this classifier.

Table 5: confusion matrix of euthymic vs depressed using nonlinear SVM

Actual	Predicted: Euthymic	Predicted: Depressed
Euthymic	27	6
Depressed	7	18

All the three models are effective in detecting euthymic subjects, whereas nonlinear SVM detects more depressed subjects compared to other models. Interestingly, the decision tree is better than linear SVM in detecting depressed individuals.

4.4 Classification of high suicide risk individuals in euthymic subjects

Here also, we employed all the three machine learning approaches, decision tree, linear SVM and nonlinear SVM classifiers to detect high suicide risk in 33 euthymic subjects.

Using a decision-tree classifier as shown confusion matrix given in Table 6, we were able to detect 16 high suicide risk subjects euthymic subjects and 6 low suicide risk subjects out of 33. The TPR is obtained as 0.76 and FPR is obtained as 0.5 We obtained an accuracy of 66.7% and AUC of 0.587 by using this classifier. Same classifier has been tested on depressed subjects which gave an accuracy of 60%.

Table 6: Confusion matrix of high vs Low suicide risk using decision tree

Actual	Predicted: High suicide risk	Predicted: low suicide risk
High suicide risk	16	5
Low suicide risk	6	6

Using linear SVM classifier as shown confusion matrix given in Table 7, we were able to detect 17 high suicide risk subjects euthymic subjects and 8 low suicide risk subjects out of 33. The TPR was obtained as 0.81 and FPR was obtained as 0.33. We obtained an accuracy of 75.8% and AUC of 0.76 by using this classifier. The same classifier has been tested on depressed subjects and gave an accuracy of 72%.

Table 7: Confusion matrix of high vs low suicide risk using linear SVM

	Predicted	
Actual	High suicide risk	Low suicide risk
High suicide risk	17	4
Low suicide risk	4	8

Using nonlinear SVM with Gaussian kernel as shown confusion matrix given in Table 8, we were able to detect 19 high suicide risk subjects euthymic subjects and 5 low suicide risk subjects out of 33. The TPR is obtained as 0.904 and FPR is obtained as 0.583. We obtained an accuracy of 72.7% and AUC of 0.722 by using this classifier. Same classifier has been tested on depressed subjects yielding an accuracy of 68%.

Table 8: Confusion matrix of high vs low suicide risk using nonlinear SVM

	Predicted	
Actual	High suicide risk	Low suicide risk
High suicide risk	19	2
Low suicide risk	7	5

In classifying high risk suicidal ideation subjects from low risk in terms of accuracy, contrary to the previous approach, linear SVM is better in performance compared to other models. However, if the objective is to detect only the high suicide risk subjects nonlinear SVM performs slightly better than linear SVM.

CHAPTER FIVE

DISCUSSION AND CONCLUSION

In this study, 72-hour activity data recordings for 58 subjects were taken. Features derived from these activity data were observed as statistically significant between euthymic and depressed individuals. The nonlinear measure, VI, correlates significantly with self-rated suicidal ideation scores taken from subjects. We implemented three classifier algorithms to differentiate euthymic subjects from depressed subjects and, using the same classifier framework, detected high suicide risk subjects.

5.1 Discussion

VI found to be a significant feature in detecting suicide risk in euthymic subjects. We have shown that nonlinear SVM with Gaussian kernel able to classify between euthymic and depressed subjects with higher accuracy compared to other models. And to classify high suicide risk in euthymic subjects linear SVM can be used. Tables 9 and 10 provide a summary of our findings.

Table 9: Classifier statistics for euthymic vs depressed

Classifier	Accuracy	AUC
decision tree	74.10%	0.76
linear SVM	69%	0.75
nonlinear SVM	77.60%	0.77

Table 10: Classifier statistics for high suicide risk in euthymic subjects

Classifier	Accuracy	AUC
decision tree	66.70%	0.58
linear SVM	76%	0.76
nonlinear SVM	72.70%	0.72

In this work, we also demonstrated that the features derived from wrist-worn activity devices along with machine learning approaches can be employed for the detection of suicide risk. The framework to implement our approach in real time is shown below.

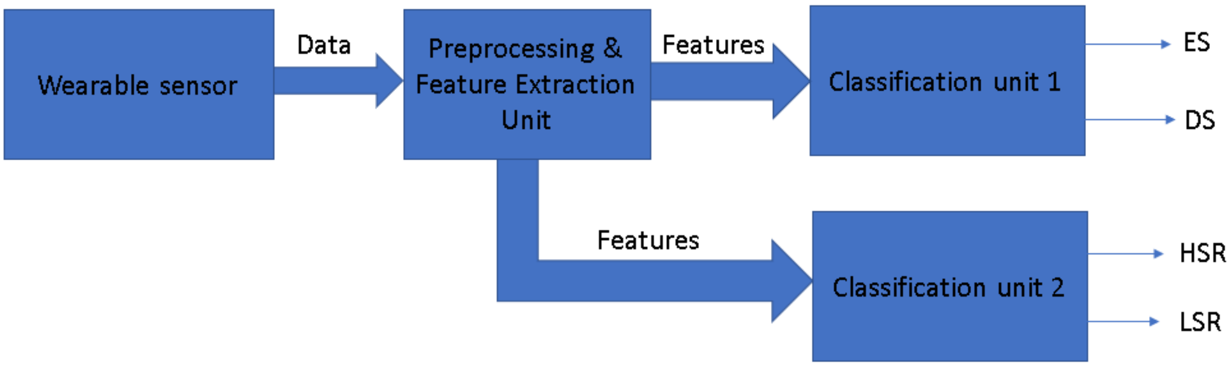

Figure 8: Framework for detecting suicide risk(ES-euthymic subject, DS-depressed subject, HSR-high suicide risk, LSR-low suicide risk)

In the above figure, collected data from wearable sensors are preprocessed and required features are extracted. These features act as input to the machine learning classification unit 1 to differentiate euthymia from depression. In our study, nonlinear SVM was found to be efficient; there may be other effective classifiers. ES represents the identified class of euthymic subjects and DS represents depressed subjects. Classification unit 2 implements the linear SVM algorithm; HSR represents high suicide risk subjects and LSR represents low suicide risk subjects.

5.2 Limitations and future work

The limitation in our work is the number of subjects used in this study is small. Suicide rate is highest among youth and veterans and individuals suffering from post-traumatic stress disorder (PTSD). Extending this work to these groups and detecting risk in those individuals could be a topic of future work. Similarly, a future study could assess whether we can apply a similar approach to clinical assessment of subjects with eating disorders. To derive features and develop an appropriate machine-learning framework we need at least 1.5 hours of data, required by the nonlinear feature VI. Although activity data may be obtained in real time, as a diagnostic procedure in a clinic, it would be good to obtain signals that have information on a shorter time scale than 1.5 hours. One plausible signal is the heart rate, as individuals with depression may also have cardiovascular problems. Hence, instead of activity features, we could explore the use of heart-rate data to detect suicide risk as a topic of future research.

5.3 Conclusion

This study demonstrated that we can differentiate between euthymic and depressed subjects and can easily be adapted for tracking suicidal ideation in real time. Therefore, a wearable device that can track the suicidal ideation noninvasively and continuously in real time may be very useful in situations where individuals are unwilling to communicate. If these devices have a capability of communicating suicide risk remotely to a clinician or a caregiver, they could be beneficial in effective management and prevention of suicide in these vulnerable individuals.

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Appendix

Calculation of VI and GWS using wavelet transform

The continuous wavelet transform of digitally acquired activity data, x_n with n=1,2, ..., N is obtained by the convolution of the data with a scaled and translated version of a mother wavelet as described previously [32]:

$$W_n(s) = \sum_{n'}^{N-1} x_{n'} \Psi^* \left[\frac{(n'-n)\delta t}{s}\right]$$

where δt = 0.1 hr, N is the total number of data points, s is the scale defined in a dyadic representation as $s_j = s_o 2^{0:5j}$ with $s_o = 2\delta t$ and 64 sub-octave per octave of the dyadic scale to obtain a total number of 577 scales with j=0,1, ... 577. $\boldsymbol{\Psi^*}$ represents the complex conjugate of the normalized wavelet function, where:

$$\Psi\left[\frac{(n'-n)\delta t}{s}\right] = \left(\frac{\delta t}{s}\right)^{1/2} \Psi_o\left[\frac{(n'-n)\delta t}{s}\right]$$

We performed this convolution with a Morlet wavelet, a plane wave modulated by a Gaussian function defined as

$$\Psi_o(n\delta t/s) = \pi^{-0.25} e^{i6n\delta t/s} e^{-0.5(n\delta t/s)^2}$$

Since the Morlet wavelet is a complex function, the obtained wavelet transformation of the data, $\mathbf{W_n(s)}$, is also complex with areal part and an imaginary part. Therefore, corresponding to each scale the amplitude is defined as A(s)=|W_n(s)|. The obtained amplitudes are in normalized units.

For scale,s, ranging from 0.19 to 1.46hr we plotted the distribution of amplitudes at each of these scales and such distributions exhibited a long tail probability function. We used gamma function, the function generally used for fitting such long tail distributions, to obtain the shape parameter $\gamma(s)$.The vulnerability index(VI) is obtained as $\int_{0.19}^{1.46} \gamma(s)ds$.The power spectrum is obtained as |**W_n(s)**|^2.The global wavelet spectrum obtained as GWS(s)= $\sum_n \frac{Wn(s)}{n} * \sigma^2$.where σ^2 is variance of the original data.